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Title

High-resolution topographical information improves tree-level storm damage models

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Abstract

Storms cause major forest disturbances in Europe. The aim of this study was to model tree-level storm damage probability based on the properties of tree and its environment and to examine whether fine-scale topographic information is connected to the damage probability. We used data documenting effects of two autumn storms on over 17000 trees on permanent Finnish National Forest Inventory plots. The first storm was associated with wet snow fall that damaged trees, while exceptionally strong winds and gusts characterized the second storm. During the storms soils were unfrozen and deciduous trees without leaves. Generalized linear mixed models were used to study how topographical variables calculated from digital elevation models (DEM) with resolutions of 2 and 10 m (TOPO2 and TOPO10) were related to damage probability, in addition to variable groups for tree (TREE) and stand (STAND) characteristics. We compared models containing different variable groups with Akaike Information Criteria. The best model contained variable groups TREE, STAND and TOPO2. Increase in slope steepness calculated from the high-resolution DEM decreased tree-level damage probability significantly in the model. This suggests that the local topography affects the tree-level damage probability and that high-resolution topographical data improves the tree-level damage probability models.

Keywords: windthrow, wind storm, wind damage, snow damage, digital elevation model

1. Introduction

Changes in climate are expected to have pronounced effects on the disturbance regime of boreal forests (Seidl et al. 2017). In Europe, storms account for a larger amount of forest damage than other disturbance types (Schelhaas et al. 2003), and storm induced damage has increased in Europe over the last 60 years (Gregow et al. 2017). Understanding storm disturbance processes is crucial for predicting climate change effects on forests, as climate induced changes in forest productivity are altered by disturbances (Lindroth et al. 2009, Reyer et al. 2017).

Wind damage probability of a tree is affected by its susceptibility to damage and the wind conditions subjected to it. As wind conditions during storms can have high spatial variance, the data about the local wind conditions affecting trees can be difficult to obtain. Local wind conditions are modified by forest management operations, such as thinnings and clear cuttings, in which trees in previously sheltered environments are exposed to stronger winds (Peltola et al. 1999, Jalkanen and Mattila 2000). Local variation in wind properties is also influenced by topography, and therefore topographical variables have often been included in statistical models of wind damage (e.g., Laiho 1987, Schmidt et al. 2010, Albrecht et al. 2012, Schindler et al. 2012). Suvanto et al. (2016) showed that, when detailed data about the wind conditions during the storms are not available, stand-level storm damage models can be improved by adding topographical variables derived from digital elevation models (DEM), when used in combination with estimated wind direction. Topographical information can also be included in storm damage models indirectly through wind field data, as near-surface wind characteristics are strongly dependent on topography. For example, Jung and Schindler (2016) and Venäläinen et al. (2017) utilized topographical data in developing high resolution wind speed data set for studying forest wind damage risk.

Tree susceptibility to damage is affected by properties such as tree species, size and shape. Probability of wind damage has been found to increase with increasing tree height (Lohmander and Helles 1987, Schmidt et al. 2010, Albrecht et al. 2012) and tall trees with relatively small diameter are particularly vulnerable to damage (Peltola et al. 1999). Norway spruce (*Picea abies* (L.) Karst) is considered more vulnerable to wind damage than Scots pine (*Pinus sylvestris* L.) (Peltola et al. 1999, Dobbertin 2002, Valinger and Fridman 2011), as its relatively shallow root system provides a weaker anchorage to the ground (Kalela 1949, Peltola et al. 2000). On the other hand, Scots pine has been found to be more vulnerable to snow damage than Norway spruce, due to differences in the crown shape between the species (Nykänen et al. 1997). In northern Europe, deciduous species have a lower risk of wind damage compared to evergreen conifers, because most storms and the strongest winds occur during autumn and winter when deciduous trees have already shed their leaves and have therefore lower wind loads (Peltola et al. 1999). Pathogens that cause wood decay and weaken trees predisposing them to abiotic damage (Whitney et al. 2001, Honkaniemi et al. 2017).

Rapidly developing remote sensing methods provide increasingly detailed information about the physical environment, including fine-scale topography. The National Land Survey of Finland (NLS) is conducting a country-wide laser scanning campaign, and the resulting data is used for creating a new 2 meter resolution DEM, which will cover the whole country by 2020 (NLS 2017a). Country-wide laser scanning data sets are being produced in other countries as well (e.g. Lantmäteriet 2017, Swisstopo 2017). In studies of forest storm damage, these data sets provide increased accuracy but also enable to consider thefine-scaled variation in topography within the close vicinity of the studied trees. While there are some examples of using fine-scale topographical data for studying wind damage in forests (see Saarinen et al. 2016), most studies have used coarser data to account for topographical variation (e.g., Schmidt et al. 2010, Anyomi and Ruel 2015, Suvanto et al. 2016) or excluded topographical variables from the analysis (e.g., Valinger and Fridman 2011).

The aim of this study was (1) to statistically model the damage probability of an individual tree during storms based on the properties of a tree and its environment and (2) to examine whether fine-scale topographic information is connected to tree-level storm damage probability. To accomplish this, we used an extensive empirical data set documenting damage to trees after two severe autumn storms in 2001, and studied how tree and stand properties, as well as fine-scale and coarse-scale topographical variables were connected to damage probability of trees.

2. Material and methods

2.1 Storm damage data

The storm damage data set was collected between November 2001 and January 2002 at permanent plots of the Finnish National Forest Inventory (NFI) after two exceptionally severe autumn cyclones Pyry (1.11.2001) and Janika (15.11.2001) (Fig. 1). The storms caused an estimated damage of 7.3 million cubic meters of stemwood (Ihalainen and Ahola 2003). Of the two storms, storm Janika was associated with stronger winds, average wind speed (10 minutes) ranging between 16 to 18 ms^{-1} and strongest measured gusts in land areas reaching 27.8 ms^{-1}. These were the highest wind speeds measured in land-areas in Finland since autumn 1959 (FMI 2001). Storm Pyry had lower wind speeds (in the study area, measured maximum 10 minute average wind speeds up to 12 ms^{-1} and gusts up to 21.9 ms^{-1} in land areas, higher close to the sea or large lakes) but was associated with wet snowfall that damaged trees. Snow fall related to storm Pyry lasted three days (30.10.-2.11.2001). The snow load on tree crowns during Pyry was estimated to 30 kg m^{-2} (Zubizarreta-Gerendiain et al. 2012). Soils were unfrozen and broad-leaved trees without leaves during both storms (Ihalainen and Ahola 2003).

In the study area, NFI follows a cluster sampling design where clusters are arranged in a grid. Every fourth cluster in the 9th National Forest Inventory in Finland (NFI9) was a permanent cluster containing 10 or 14 plots (Tomppo et al. 2011). On permanent clusters the tree locations on plots were mapped, which enabled the identification of trees in a re-measurement conducted after the storms in 2001. The trees included in plots were selected using angle count sampling with basal area factor 2 and maximum radius of 12.52 m (Tomppo et al. 2011).

The storm damage data covers a total of 1826 NFI9 plots in altogether 276 NFI9 permanent clusters in southern and western Finland, and includes a total of 17686 trees of which 220 had been damaged in the storms (Fig. 1, Ihalainen and Ahola 2003, Suvanto et al. 2016). However, we excluded standing trees classified as dead or dying in the NFI9 measurement (287 trees), as well as conifers other than Norway spruce and Scots pine (18 trees). The high-resolution digital elevation model was not available for the whole study area and trees located in the areas of missing data were excluded from the analysis (804 trees). Therefore, the final data set contained 16577 trees (of which 202 were damaged) in 1730 NFI9 plots within 267 clusters (Table 1). Different types of storm caused damage were represented in the data set. Most common damage types in the data were uprooting (42 pines, 79 spruces and 4 deciduous trees) and stem breakage (25 pines, 12 spruces and 6 deciduous trees). The rest of the damaged trees were classified as leaning trees (10 pines and 9 spruces), damaged standing trees (2 spruces) or damaged trees that had already been removed and damage type could not be determined (3 pines, 9 spruces and 1 deciduous tree).

Variables describing stand and tree characteristics were extracted from the storm damage data as well as from the NFI9 data collected at the plots before the storms (1996 to 1999). Stand-level variables included stand age, basal area (BA), type and timing of recent management operations, soil type, presence of decayed standing trees in the stand and presence of new open area within 40 meters from the plot center (estimated by the field crew). Only open stand borders in the direction of the storm wind were considered and borders towards permanently open areas, such as lakes and agricultural fields, were not considered. Forest management variables included information about the type of the cutting (thinning or regeneration cutting) and the time of the cutting (last five or last ten years). As clear-cut stands were excluded, regeneration cuttings contained seed and shelter tree cuttings that leave 30 to 300 stems per hectare.

Tree-level variables included tree species, tree height, stem diameter at breast height (1.3 m, DBH), relative DBH (the ratio between DBH and the stand average DBH), and height-to-DBH ratio. Tree height was measured in the field only for every seventh tree in each plot. For the rest of the trees we used height predictions based on a model by Eerikäinen (2009), which uses DBH, tree species, and site and stand properties as predictors.

We attempted to account for the spatial variation in storm severity by using meteorological data from the storms, i.e. maximum wind speeds in storm Janika and snow accumulation in storm Pyry. However, as the spatial resolution of the available data was low and it was not possible to separate the occurred damage in the data between the two storms, these variables were left out of the final analysis. Insufficiency of coarse scale weather data in predicting storm damage has been shown before, for example, by Schindler et al. (2009).

2.3 Topographical variables

In the study area, elevation ranges from the sea level to 229 meters above sea level. Elevation increases gradually with distance from the sea and local variations in elevation are relatively low: average difference in elevation between a tree location and its surroundings within one kilometer radius was 5.1 meters while maximum difference was 44.3 meters. Variables describing the topography in the neighborhood of the trees were calculated from the NLS digital elevation models in two resolutions: 2 m (DEM2) and 10 m (DEM10). DEM2 is based on NLS laser scanning data with a point density of at least 0.5 points per square meter, whereas DEM10 is produced with contour lines, ground surface points digitized in a stereo workstation environment and elevational information in the objects of NLS Topographical database. The elevation accuracy is 0.3 meters in DEM2 and 1.4 meters in DEM10 (NLS 2017a, NLS 2017b). The laser scanning data used for producing DEM2 has been collected after the studies storms in year 2001 and, therefore, it could not be used for extracting information about tree characteristics in this study.

From both DEMs slope angle and direction as well as topographic position index (TPI) with different radii (10, 20 and 30 m for DEM2 and 50, 100, 150, 500 and 1000 m for DEM10) were calculated with the R package *raster* (Hijmans 2016). TPI describes the relative topographical position of a location in relation to its surroundings and is calculated as a difference of elevation in a location to the mean elevation within a defined radius (Guisan et al. 1999, Gallant and Wilson 2000). Negative values of TPI mean that a location is at lower elevation than its surroundings, and thus better shelter from wind, whereas positive values indicate locations higher than their surroundings, and thus higher wind exposure.

Values from all topographic variables were extracted for each tree location. To reduce the error in the tree locations, coordinates of the midpoints of the permanent NFI plots were taken from the more recent 11th NFI (2009-2013) with more accurate positioning of the plots. To account for uncertainty in the positioning of the tree locations, a mean (median for slope direction) of the neighboring cells, with cell center within a three meter radius from the tree location, was used for variables calculated from DEM2. Slope direction was transformed into a class variable describing whether the slope was directed towards the storm wind or sheltered from it (using wind direction 337.5° as the main wind direction of the storms was north to north-west. Detailed data of the near-surface wind direction was not available). If slope steepness was lower than 1° slope direction was set to wind side (Fig. 2).

2.4 Statistical methods

Storm damage probability of an individual tree was modeled with a mixed effects logistic model, where the response variable described whether or not a tree was damaged in the storms (0/1). The model was fitted in SAS (version 9.4, SAS Institute Inc. 2017) using procedure GLIMMIX. Random effects were used to account for the hierarchical structure of the data, resulting from the clustered sampling design of the NFI. Two-level nested random effects were used for the intercepts, as trees were located in plots and plots in clusters.

In the 9th NFI, the maximum radius of angle count plots was restricted to 12.52 meters. In angle count plots sampling probability is proportional to the basal area of a tree. However, as plot radius was restricted, large trees with a DBH larger than 35.4 cm were underrepresented in the data. Therefore, multi-level weights were used in the model to have the representation of tree sizes match an unrestricted angle count plot. The inverse value of the difference in tree sampling probability between an ordinary angle count plot and the restricted diameter angle count plot was used in calculating tree-level weights. Thus, trees with diameter less than 35.4 cm were assigned weight 1, while for larger trees the weight calculated as $1/(A_{restricted} / A_{unrestricted})$, where $A_{restricted}$ was the area of the 12.52 m radius plot and $A_{unrestricted}$ was the DBH dependent area from which tree would have been included in an angle count plot if the plot radius was not restricted. The weights were then scaled by setting the sum of weights within each plot to correspond to the actual number of measured trees in the plot, following the "method 2" in Pfeffermann et al. (1998) and Rabe-Hesketh and Skrondal (2006). On plot and cluster levels all observations were given weight 1.

The independent variables were divided into five variable groups containing variables related to tree characteristics (TREE), stand characteristics (STAND) and topographic characteristic calculated from two different resolution DEMs (TOPO2 and TOPO10). All continuous independent variables were scaled to have a mean of 0 and standard deviation of 1 (Table 3). Thus, the model intercept is interpreted as the expected value when all the continuous predictor variables are set to their means and the coefficient estimates between predictor variables are more comparable to each other. A logarithm transformation was tested for all continuous variables by comparing models with and without transformation with Akaike Information Criteria (AIC, Akaike 1974).

Collinearity between independent variables in the final variable groups was checked with Pearson product-moment correlation coefficients between continuous variables. The correlations were well below 0.7 except for the correlation between slope steepness values calculated from DEM2 and DEM10 ($r = 0.73$, $p < 0.001$). When the variables were log-transformed, all the correlations were below 0.7.

In a preliminary model selection variables were first chosen based on a priori knowledge of factors affecting storm damage. Different combinations of variables were then tested and variables were excluded from the variable groups if they showed small effect sizes (i.e., had negligible effect on damage probability in the model), counterintuitive coefficient signs (for example, if damage probability were to decrease with increasing wind exposure) or had large p-values. In addition, AIC values of models with and without a variable were compared before a decision was made to exclude variables.

Models were fitted with different combinations of variables groups (TREE, STAND, TOPO2, TOPO10) and then compared using AIC, AIC weights (w_i), as well as receiver operating characteristic (ROC) curves and area under curve values (AUC). AIC measures the relative quality of the model, so that lower values of AIC indicate a better model. AIC weights were also calculated for the models. The weights add up to 1 for the considered set of models and are interpreted as the weight of evidence in favor of a model being the Kullback-Leibler best model, assuming that one of the considered models is the best model (Burnham and Anderson 2002). ROC curves and AUC values describe the model's ability to discriminate between damage events and non-events (see Hosmer et al. 2013).

3. Results

In the preliminary model building process several candidate variables were left out of the models. From the TREE variable group DBH, relative DBH and height-to-DBH ratio were excluded and species were grouped to a two-class variable separating coniferous and deciduous species. Stand age, stand basal area, soil type and timing of the last cuttings were left out from the STAND variable group. In addition, type of last cutting was grouped into only two classes where regeneration cutting (for example seed or shelter tree cutting) formed one class and thinning and no cuttings formed another class. In the TOPO groups the topographic position index (TPI) variables as well as the interaction between slope steepness and direction were left out of the final models. The meteorological variables describing the storm conditions were not included in the models, as they were not statistically significant and had illogical, negative coefficients (results not shown). The variables included in the variable groups that were used in the final model comparisons are described in Table 2.

The best model, chosen by ranking the alternative models by AIC, contained variable groups describing tree and stand properties and fine-scale topographical information (TREE+STAND+ TOPO2, Table 4). The AIC weight (w_i) for the TREE+STAND+TOPO2 model was clearly higher than for the other models. The second ranked model in the AIC comparison also contained TOPO2 variable group (model TREE+STAND+TOPO2+TOPO10, Table 4). In TOPO2 and TOPO10 variable groups slope steepness (SLOPE) had a negative coefficient, implying a decreasing damage probability in steeper slopes (Table 5, only shown for the first ranked model).

TREE variables (conifer/deciduous species and height) were the most important single group accounting for damage probability. The other models with only one variable group (TOPO2, STAND, TOPO10) were last in the AIC comparison, with AIC weights close to 0 and low AUC values (Table 4). The coefficients of variables in the TREE group showed an increasing damage probability with increasing tree height for conifers, and lower damage probability, as well as decreasing damage probability with tree height, for deciduous trees (Table 5).

The STAND variable group was included in the best model with the lowest AIC (Table 4). Model coefficients showed higher damage probability in the proximity of new open stand borders (OPENAREA) and in stands where regeneration cuttings had been made within ten years (from NFI9 measurement).

For the models ranked highest, the AUC values, which describe the models ability to discriminate between damage and non-damage events, were slightly under 0.7, which is often taken as a threshold of acceptable discrimination (Table 4, Fig. 3). The best model to reach the 0.7 threshold was TREE + STAND + TOPO2, and similar AUC values were found for other top models of the AIC comparison. The lowest AUC values were found for one variable group models TOPO2 and TOPO10 (Table 4).

4. Discussion

Our results demonstrate that the high-resolution topographical data, describing local variations in topography, provides useful information about the storm damage probability of trees. Fine-scale topographical variables proved to work better than variables calculated from the coarser scale DEM. Using high-resolution data with high elevation accuracy is useful especially in tree-level studies, where it can be used to characterize the local neighborhood of a tree in detail. However, understanding the fine-scaled factors driving tree-level vulnerability to damage is also important for larger scale studies, as shown by Seidl et al. (2014) who found that neglecting spatial and structural within-stand heterogeneity weakened the outcome of wind disturbance models.

The use of laser scanning data as a source for elevation models not only enables the improvement of data resolution but also improves the accuracy of the data. Due to the difference in methods in creating the elevation models the high-resolution DEM2 has significantly better elevation accuracy than the older DEM10. This in part also explains the better performance of variables calculated from DEM2 in the storm damage models.

Not all studies have found topography to be useful in modeling storm damage. Albrecht et al. (2012) gave three possible explanations for why topography was not found to affect damage probability in their study: (1) variables describing stand and tree characteristics were superior to geographical conditions such as topography, (2) the used variables were not suitable for describing the conditions affecting damage probability, and (3) the data set did not contain extremely exposed sites where the effect of topography would have been clear. While the two first explanations are in line with our results, the third one is not supported by our results. The results showed that topography was connected to storm damage probability, even though our study area is characterized by a gentle topography with only small variations in elevation. This is in contrast with some previous studies suggesting that non-significant effect of topography was caused by low topographic variation of the study area (Anyomi and Ruel 2015, Saarinen et al. 2016).

The choice of variables calculated from DEMs is crucial for effectively describing the local wind conditions. In addition to topographical variables included in this study effects of topography on wind conditions have been described with different indices, such as distance-limited topographical exposure (TOPEX), which is calculated as sum of maximum angle to the ground in eight directions (Quine and White 1998, Scott and Mitchell 2005). The used spatial scale may also influence the functioning of the used variables. While the interaction of slope steepness and slope direction was found to significantly affect stand-level damage probability in another study using the same data set as used here (Suvanto et al. 2016), only slope steepness was significant in this tree-level study. Slope direction calculated from a high-resolution DEM may vary locally a lot (Fig. 2) and therefore may not describe well the location's exposure to wind. The significant effect of slope steepness may be related to locations with high slope steepness being associated with more variable topography in general, and being therefore more sheltered from wind. In addition, high-resolution slope steepness may be correlated to other variables than wind that are related to storm damage. For example, topography is related to soil properties, which in turn affect the support trees have against uprooting (Peltola et al. 1999).

While fine-scale topographical variables were included in the model with lowest AIC, they did not perform well alone (i.e., the TOPO2 model in Table 4). Instead, the results show that of the studied variable groups, tree properties are most clearly linked to storm damage probability, as the TREE model had clearly lower AIC values, higher AIC weights and higher AUC values compared to the other models with only one variable group (Table 4). Similar results emphasizing the importance of tree species and height have been reported in previous studies (Lohmander and Helles 1987, Schmidt et al. 2010, Albrecht et al. 2012).

The TREE variable group consisted of tree species group (conifer or deciduous), tree height, and interaction term of these two. Norway spruce and Scots pine were grouped into one class as their difference was not significant in the models. Previous studies have shown differences between the species (Nykänen et al. 1997, Dobbertin 2002, Valinger and Fridman 2011). However, the storm damage in our data set contained both wind and snow related damage. This may have reduced the difference between the two conifer species, as spruce is considered to be more vulnerable to wind and the crown shape of pines may expose them to snow damage. It is also possible that the damaged deciduous trees in the data have been mostly damaged by snow, as the damaged deciduous trees were smaller than average (Table 1) and model results for deciduous trees showed decreasing damage probability with tree height, which is atypical for wind damage.

The STAND variable group showed increased damage probability in stands after regeneration cuttings, which in this data are seed and shelter tree cuttings that leave 30 to 300 stems per hectare to the stand. Increased damage probability was also found for trees close to open stand borders (OPENAREA variable). This effect results from increased wind load after the cutting or at newly created stand border on trees that have not been acclimated to strong winds (Lohmander and Helles 1987, Peltola et al. 1999, Jalkanen and Mattila 2000). The model also showed increased damage risk of trees in stands where decay in living trees had been documented. Wood decay decreases stem strength and tree anchorage and, therefore, increases the vulnerability of the tree to wind damage (Honkaniemi et al. 2017). Stand level information about decay was selected in this study instead of tree-level information because wood-decay in living trees is difficult to detect in the field (Mattila and Nuutinen 2007). Yet, if there are trees in the stand that are visibly affected by wood-decaying fungi (e.g. *Heterobasidion* sp.) the probability of decay in other trees in the same stand is also higher.

The location accuracy of the trees is a source of uncertainty in the topographical variables as there is necessarily some error involved in the GPS positioning of the NFI plots. In this study, we aimed to control this effect by calculating the high-resolution topographical variables as the average values of grid cells within three meters from the tree location. Yet, it is still likely that inaccuracy in the tree locations causes uncertainty to the DEM2 variables.

The statistical significance of individual variables is affected by the size of the data set. Even though the data set is large, the proportion of damaged trees was rather low (~1.2% of the data) in comparison with many other studies (e.g., Schmidt et al. 2010, Kamimura et al. 2016). A larger data set, especially a larger number of damaged trees, would be useful in specifying the factors affecting damage probability.

Our results demonstrate the connection between fine-scaled topographical variation in a tree's neighborhood and the storm damage probability of a tree. Topography affects tree damage probability indirectly, through its effects on other factors such as wind and soil characteristics. Thus, the effects of fine-scaled topography should be taken into account in calculation of these variablles, as most of the available data sets are based on input data of coarser resolution than the DEMs used in this study (e.g., Jung and Schindler 2016, Venäläinen et al. 2017). When high-resolution topographical information is available, it should be considered in future studies of storm damage in forests, either as topographical variables or as an inputs for variables describing the direct factors affecting the damage probability.

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Table 1. Details about the storm damage data: number of trees, DBH (cm) and tree height (m) in damaged and undamaged trees for different species.

	No damage	Damage	All
Number of trees			
All species	16375	202	16577
Scots pine	6447	80	6527
Norway spruce	6793	111	6904
Broad-leaved	3135	11	3146
DBH (mean ± st. deviation)			
All species	20.07 ± 9.35	23.98 ± 9.89	20.11 ± 9.37
Scots pine	20.64 ± 8.83	21.42 ± 7.98	20.65 ± 8.82
Norway spruce	21.45 ± 9.46	26.88 ± 10.30	21.54 ± 9.50
Broad-leaved	15.87 ± 8.93	13.36 ± 5.04	15.86 ± 8.92
Height (mean ± st. deviation)			
All species	16.34 ± 5.85	18.91 ± 5.87	16.37 ± 5.86
Scots pine	15.57 ± 5.47	16.56 ± 4.90	15.58 ± 5.46
Norway spruce	17.47 ± 5.92	21.05 ± 5.85	17.53 ± 5.93
Broad-leaved	15.47 ± 6.06	14.54 ± 3.21	15.47 ± 6.05

Table 2. Description of variable groups and independent variables used in the final models. In categorical variables the class mentioned first is used as the reference class in the models (i.e. parameters are estimated only to the other classes).

	data type	units/classes	data source
TREE			
Species group (SPECIES)	categorical	conifer, deciduous	NFI9
Tree height (HEIGHT)	numeric	cm	NFI9
STAND			
Cutting in the last 10 years (CUTTYPE)	categorical	none or thinning, regeneration cutting	NFI9, storm data
Decay in stand	categorical	absent, present	NFI9
New open area in wind direction (OPENAREA)	categorical	absent, present	storm data
TOPO2			
Slope steepness (SLOPE)	numeric	degrees	DEM2
TOPO10			
Slope steepness (SLOPE10)	numeric	degrees	DEM10

NFI9 – 9^{th} National Forest Inventory, storm data – described in section 2.1, DEM2 – 2 m resolution digital elevation model, DEM10 – 10 m digital elevation model.

Table 3. Parameters used for scaling the continuous variables in the final models. Scaling to mean 0 and standard deviation 1 were calculated as $X_{scaled} = (X - \mu) / \sigma$.

Variable	μ	σ
log(HEIGHT)	2.72	0.43
log(SLOPE + 0.1)	1.24	0.82
log(SLOPE10 + 0.1)	0.58	1.55

Table 4. Comparison of models with AIC, difference in AIC compared to the best model (ΔAIC), AIC weights (w_i) and AUC. For the explanations of the variable groups, see Table 2.

Model	AIC	ΔAIC	w_i	AUC
TREE + STAND + TOPO2	1551.58	0.00	0.48	0.70
TREE + STAND + TOPO2 + TOPO10	1553.44	1.86	0.19	0.70
TREE + STAND	1554.22	2.64	0.13	0.70
TREE	1554.37	2.79	0.12	0.66
TREE + STAND + TOPO10	1554.92	3.34	0.09	0.70
STAND	1576.76	25.18	0.00	0.62
TOPO2	1577.12	25.54	0.00	0.51
TOPO10	1579.51	27.93	0.00	0.53

Table 5. The fixed effect results and the covariance parameter estimates for the random effects (clusters and plots nested within clusters) of the best model. For the explanations of the fixed effects variables, see Table 2. Note that continuous variables were scaled before model fitting, parameters used in scaling can be found in Table 3.

Fixed effects	Estimate	St.Error	DF	t value	Pr > |t|
Intercept	-9.92	0.36	266	-27.95	<.001
TREE					
$SPECIES_{deciduous}$	-1.32	0.60	262	-2.19	0.030
log(HEIGHT)	0.55	0.17	16303	3.23	0.001
$SPECIES_{deciduous}$: log(HEIGHT)	-0.76	0.26	16303	-2.87	0.004
STAND					
OPENAREA	0.93	0.25	154	3.67	<.001
$CUTTING_{regeneration}$	1.17	0.51	71	2.29	0.025
DROT	0.84	0.42	57	2.01	0.050
TOPO2					
log(SLOPE)	-0.36	0.15	16303	-2.48	0.013

Random effects	Estimate	St. Error
Cluster	2.68	0.79
Plot (Cluster)	34.00	5.27

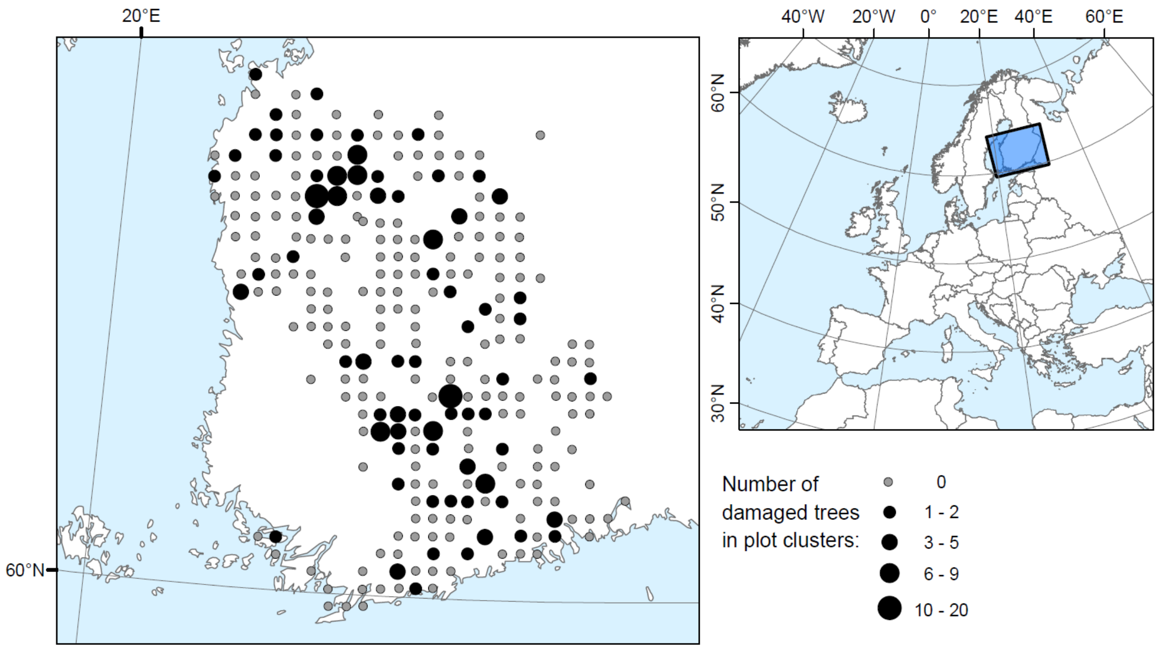

Figure 1. Map of the study area. The NFI9 plots where the storm damage data is collected from are shown in the figure on the left, the size of the dot refers to number of damaged trees in each plot cluster.

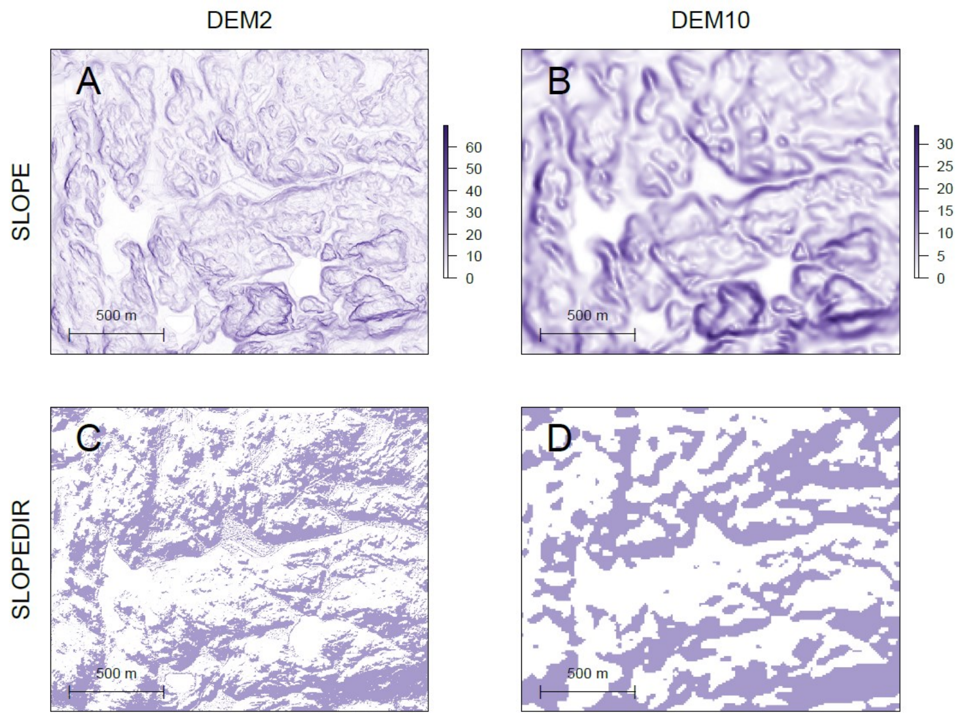

Figure 2. Examples of the topography variables calculated for the same area from digital elevation models (DEM) with different resolutions: Slope steepness (degrees) calculated from 2 meter resolution DEM (DEM2) (A) and 10 meter resolution DEM (DEM10) (B), slope direction, with shelter side shown as shadowed, calculated from DEM2 (C) and DEM10 (D). Top of the figures are towards north.

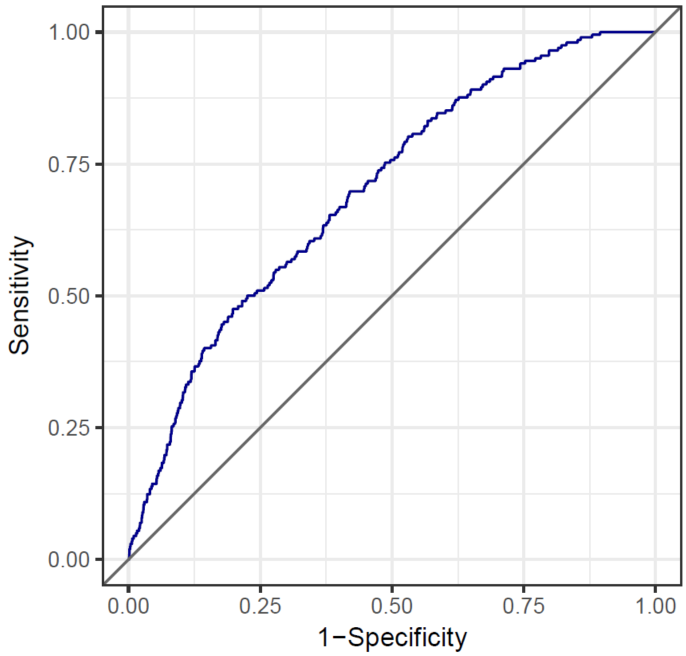

Figure 3. ROC curves of the model with the lowest AIC. The curve illustrates the discrimination ability of the model and shows the model's sensitivity (true positive rate) and 1-specificity (false positive rate) with different classification thresholds. Area under the curve (AUC) = 0.70.